

**Climatology-Calibrated Precipitation Analysis at Fine Scales:
Statistical Adjustment of STAGE IV towards CPC Gauge-Based Analysis**

Dingchen Hou^{1,2,*}, Mike Charles^{1,3,**}, Yan Luo^{1,3},
Zoltan Toth^{1,***}, Yuejian Zhu¹, Roman Krzysztofowicz⁴,
Ying Lin¹, Pingping Xie⁵, Dong-Jun Seo⁶, Malaquias Pena^{1,2} and Bo Cui^{1,2}

1. *Environmental Modeling Center/NCEP/NWS/NOAA, Camp Springs, MD*
2. *I. M. Systems Group, Inc., Camp Springs, MD*
3. *Science Application International Corporation, Camp Springs, MD*
4. *University of Virginia, Charlottesville, VA*
5. *Climate Prediction Center/NCEP/NWS/NOAA, Camp Spring, MD*
6. *Office of Hydrologic Development/NWS/NOAA, Silver Spring, MD*

** Current Affiliation: Climate Prediction Center/NCEP/NWS/NOAA, Camp Springs, MD

*** Current Affiliation: Global System Division/ESRL/OAR/NOAA, Boulder, CO

12/16/2010

To be submitted to *Journal of Hydrometeorology*

** Corresponding author address:*

Dr. Dingchen Hou,
Environmental Modeling Center/NCEP/NWS/NOAA
5200 Auth Road,
Camp Springs 20746

Abstract

Bias correction and downscaling of NWP precipitation forecast requires an accurate and quality controlled analysis as the proxy for the truth, on a 5x5km (NDFD) grid over CONUS for each 6-hour period. The two widely used precipitation datasets are the CPC Unified Global Daily Gauge Analysis and Stage IV analysis based on Quantitative Precipitation Estimate with multi sensor observations. The Former is based on gauge records with a uniform quality control across the entire domain and thus bears more confidence, but it provides only 24 hour accumulation at one eighth degree resolution. The Stage IV dataset, on the other hand, has the required spatial and temporal resolution, but is subject to different methods of quality control and adjustments by different River Forecasting Centers.

This paper describes a methodology used to generate a new dataset by combining the two available analyses to take advantage of the higher climatological reliability of the CPC dataset and the higher temporal and spatial resolution of the Stage IV dataset. The Stage IV dataset is first aggregated to CPC resolution and a statistical relationship is established between the two datasets. Simple linear regression is used to adjust the aggregated Stage IV data to make its climatology look like that of the CPC dataset. Finally, the adjusted Stage IV data is downscaled back to its original resolution to recover its original variability in time and space.

The new data set, named Climatology Calibrated Precipitation Analysis (CCPA), is evaluated with quantitative comparison against CPC analysis and RFC observations. It is shown that CCPA retains spatial and temporal patterns of Stage IV data set while making its long term average closer to that of CPC analysis and the improvement is more significant with lower and medium daily precipitation amounts. Cross validation suggests that the methodology is robust but subject to limitations due to the validity of the linear regression model and the relative scarcity of heavy precipitation events.

1. Introduction

Bias correction and downscaling of numerical weather prediction (NWP) products such as temperature and wind, of the NCEP Global Ensemble Forecasting System (GEFS) and the North America Ensemble Forecasting System (NAEFS), have demonstrated significant benefits in improving local forecasts over CONUS domain. The application of the same procedures to precipitation is hindered by the lack of a satisfying precipitation dataset. The required dataset should be our best estimate for truth on a 5 x 5 km (NDFD) grid for each 6-hour period, and it should be accurate and quality controlled.

Atmospheric scientists and hydrologists have been studying the behavior of precipitation over a wide range of spatial and temporal scales. However, due to paucity of data and the intermittency of precipitation, especially precipitation associated with cumulus convection, analysis of observed rainfall distributions is often compromised as a trade-off between spatial and temporal resolution: for example, hourly fields at catchment scales (Onof and Wheeler 1996) versus monthly means at global scales (Chen et al. 1996).

Objective techniques have been developed and applied to construct analyzed fields of precipitation over global land areas from surface gauge observations (e.g. Xie et al. 1996; Chen et al. 2002). Space-borne measurements of precipitation, with continuous developments and refinements of retrieval algorithms, has yielded operational precipitation products based on satellite observations of infrared (Arkin and Meisner 1987; Susskind et al. 1997; Xie and Arkin 1998), passive microwave (Wilheit et al. 1991; Spencer 1993; Ferraro 1997), and space-borne precipitation radar (Kummerow et al.

2000). Although combining information from multiple satellite sensors as well as gauge observations and numerical model outputs yield analyses of global precipitation with stable and improved quality (e.g. Huffman et al. 1997; Xie and Arkin 1997; Huffman et al. 1997; Xie et al. 2003), the merged precipitation products have one deficiency, i.e. their quantitative uncertainty over land (e.g., Nijssen et al. 2001; Fekete et al. 2004).

Among the individual inputs used to define the combined precipitation analyses, both the satellite estimates and the model predictions are indirect in nature and need to be calibrated or examined using the gauge observations (e.g. Ebert and manton 1998; McCollum et al. 2002). Therefore, Gauge observations play a critical role in constructing precipitation analyses over land and gauge-based monthly precipitation analysis has been constructed over the global land domain (e.g. Xie et al. 1996; Dai et al. 1997; New et al. 2000; Chen et al. 2002). Similar analyses on sub monthly time scales are relatively new due to limited accessibility of corresponding station observations from many countries. Nevertheless, NCEP Climate Prediction Center (CPC) Unified Global Daily Gauge Analysis (Xie et al. 2010) has generated products over global land areas. This analysis is defined by interpolating quality controlled gauge reports at ~30K stations over the global land areas using the algorithm of Xie et al. (2007) and the number of reporting stations over CONUS is about ~12K. For the purpose mentioned earlier, this CPC data set bears more confidence but it provides only 24 hour accumulation at one eighth degree spatial resolution.

During the last decade or so, the advent of high spatial and temporal resolution precipitation analysis over the Contiguous (or conterminous) United States (CONUS) made tremendous progress by combining gauge and radar observations. Currently, each of the 12 River Forecast Centers (RFC) of NOAA National Weather Service (NWS) routinely produces a multi-sensor precipitation analysis over its own domain and these analyses from individual RFCs are mosaicked at NCEP into a national product, called the NCEP Stage IV. Stage IV precipitation analysis provides an unprecedented database at scales that are sufficiently fine.

The Stage IV precipitation data set is used in the construction of precipitation statistics at scales that are sufficiently fine to be of hydrologic relevance (Kursinski and Mullen, 2008). It is also used as input to hydrological models (Chen et al. 2007) and used as truth for model verification (Zhao and Jin, 2008). As it has a spatial resolution nearly equal to NDFD grid and temporal resolution of 6 hours, it is an excellent candidate to be used as the truth for bias correction and downscaling of precipitation forecast product. However, the product is subject to different methods of quality control and adjustments by different River Forecasting Centers. Although the implementation of Doppler radar at the national level has greatly improved precipitation estimates, serious limitations still exist. Despite its fine spatiotemporal resolution, caution must be employed when analyzing Stage IV data because of the uncertainty of radar retrievals in regions of complex terrain or melting hydrometeors. Specifically, limited radar coverage at low levels above ground level, especially in the interior of the West, wide spread beam blockage over the Intermountain West and the shallow nature of stratiform orographic precipitation, among other factors,

all post uncertainties to the analysis (Maddox, 2002). For this reason, some users restrict their analysis to the region east of 105W and places highest confidence east of 100W (Kursinski and Mullen, 2007).

To provide a better proxy of the truth for the precipitation field over CONUS, it is apparently required to take the advantages of the higher climatological reliability of the CPC dataset and the higher temporal and spatial resolution of the Stage IV dataset. We describe the development of such a new dataset by combining the two available datasets for this purpose. This paper is organized as follows: Section 2 provides descriptions of the Stage IV and CPC datasets used in the study; Section 3 describes the methodology, including the statistical algorithm and the related application procedures while the implementation of the new product and generation of the historical data set are given in section 4. Qualitative and quantitative evaluations of the methodology and the new data set are presented in section 5 and concluding remarks and further discussions are offered in section 6.

2. Input Data Sets

CPC continuously collects gauge observations, perform basic quality control and conduct an early run of its Unified Global Daily Gauge Analysis procedure to generate a temporal version of the daily analysis on a regular basis. After the missing data are collected and extensive quality control is performed, a final version of the 24-hour accumulated precipitation can be generated. For this study, CPC provided the final analysis over CONUS land domain, as 24-hour accumulations each day (12Z-12Z) at 0.125 latitude x

0.125 longitude mesh, for the period from Jan. 1 2000 to Dec. 31 2006. As the final analysis for 2007 and later years was not available, the temporal version is used for the period of Jan. 1, 2007 through Nov. 6, 2009. By mixing the two different versions, the sample size is increased with assumption that the statistical difference between the temporal and the final version of the CPC analysis can be neglected. For simplicity, this dataset is referred as CPC.

The National Centers for Environmental Prediction (NCEP) generates Stage IV precipitation analyses (Lin and Mitchell 2005), providing area-averaged, hourly and 6-hourly estimates of precipitation on a 4-km pixel over the CONUS. The analysis is based on multi-sensor observations. The radar and rain gauge measurements are merged at the 12 River Forecast Centers (RFC) that produce regional analyses over their corresponding domains (see Fig.1) and these regional products are then mosaicked into a national product at NCEP. The procedure has been operationally running and the products being archived since Jan. 1, 2002. The data used in this study consist of 6-hourly (12-18Z, 18-00Z, 00-06Z, 06-12Z) accumulations on the 4 km hrap grid and span more than eight years from 2002 to 2010 with only a few files corrupt or missing. Unlike the CPC data which is defined only over CONUS land area, Stage IV analysis extends out of CONUS coast and the political boundaries to cover some offshore areas and some bordering regions of Canada and Mexico (Fig. 2). In this paper, ST4 is used sometime to refer to the Stage IV data.

3. Methodology and Algorithms

The methodology employed is basically statistical adjustment of the Stage IV data towards CPC so that their long term means are closer. The 6-hourly accumulations in the Stage IV dataset are first aggregated to the resolution of the CPC, i.e., daily accumulation over 0.125 latitude x 0.125 longitude grid boxes. As the next step, a statistical relationship is established between the two datasets at CPC resolution and used to adjust the aggregated Stage IV data to make its climatology (limited to the mean in this paper) look like the CPC dataset. Finally, the adjusted Stage IV data is downscaled back to its original resolution to recover the highly desired variability in time and space.

a. Aggregation of 6 hourly Stage IV to daily accumulation at CPC grid

In order to adjust the stage IV data toward the climatology of CPC, one needs to establish a statistical relationship between the two analyses. As CPC has lower resolution in both space and time, the first step of the procedure is to aggregate the stage IV data to the resolution of the CPC data set. The four 6-hour accumulations from 12 UTC of a specific day to 12 UTC next day is first aggregated into a single 24-hour accumulation for the day in consideration. Mathematically, this is written as

$$ST4_{H,24h} = \sum_{n=1}^4 ST4_{H,6h}^n \quad (1)$$

where the subscript H indicates the higher spatial resolution associated with the original hrap grid of the stage IV data, which it self is abbreviated as ST4. The next step is interpolating $ST4_{H,24h}$ to the CPC 0.125 latitude x 0.125 longitude grid (indicated by subscript L), symbolically written as

$$ST4_{H,24h} \rightarrow ST4_{L,24h} \quad (2)$$

with the arrow representing an interpolation/extrapolation scheme carefully designed to conserve the water volume in the area covered by each grid box of the coarse grid.

When equation (2) is reversed, i.e., the aggregated raw stage IV data is converted from the lower resolution back to the higher resolution grid, the resulted $ST4_{L-H,24h}$ is different from $ST4_{H,24h}$ due to the information loss in the extrapolation. Here the subscript L-H represents an interpolation from the lower resolution grid to the higher resolution grid. Nevertheless, the ratio between the two fields at each grid points can be used to recover the lost information of the fine scale patterns.

b. Linear regression for each day of the year and each CPC grid box

As discussed in section 2, both CPC and Stage IV data sets are available for the period of Jan. 1 2002 to Nov. 6 2009. The purpose of the statistical adjustment of stage IV data is to make its climatology close to that of the CPC data. The existence of complicated geographic patterns and orographic features in space and domination of annual cycle or seasonal variation in the precipitation observation and analysis (Chen et al. 2002; Xie et al. 2007) suggests that climatology is better to be defined at each grid box for each day of the year.

With just 7 years of data coverage the two data sets may not be sufficient to define the climatology of each data set. In order to increase the sample size, a 61-day window is used by including the 30 days before and after the day in consideration with a maximum sample size of 427. This choice of the width of the window is the result of compromise

between a reasonable actual sample size (rain days) at most grid points for most days and relatively uniform samples. As only the rain days indicated by Stage IV are counted, the actual sample size is dependent on the geographic location of the grid box and the season. Fig. 3 shows the actual sample size for Jan. 1 and July 1, as two examples. With this 61 day window, the actual sample size in Eastern US is over 200 for most cases, while empty sample is encountered over the Southwestern desert during the summer months (May to September). The time series of actual sample size N for a grid point in the desert is shown in Fig. 4.

Various statistical schemes are used to adjust precipitation estimate and forecasts. Probability mapping is widely used in calibration of forecast against observation, as the two may have very different distributions. In this study, a simple linear regression is employed after some initial tests. The initial adjustments at each RFC have removed extreme values of precipitation and the continuous distribution function in stage IV is well behaved. We admit that this is not the best algorithm but it provides a straight forward solution to the problem. For each CPC grid box and each day of the year, the stage IV precipitation is regressed to the value of CPC, i.e.

$$CPC = a * ST4_{L,24h} + b \quad (3)$$

where a and b are the slope and intercept, respectively, of the linear regression, and the sub-scripts of CPC and ST4 are used to emphasize the spatial and temporal resolution of the two precipitation analyses.

c. Gap filling and temporal smoothing of the regression coefficients

Fig. 5a displays the maps of the regression coefficients a and b , and the gaps due to empty data sample is clear. As discussed earlier and shown in Figs. 3 and 4, the actual sample size is very small adjacent to these gaps in the southwestern US during the summer months. This makes the estimated regression coefficients less reliable. Another problem with this regression is that the slope is very large at a few special grid points, with maximum being over 100 (see Fig. 6). A careful investigation suggests that these extreme slopes occur over the Pacific costal areas where stage IV precipitation is systematically smaller than CPC by one or two orders of magnitude. This may be caused by systematic differences in the algorithms of the two analyses and remain to be further investigated. Apparently, this is out of the focus of the current study. Instead, these abnormally large coefficients are assumed to be representative and used to adjust the extremely small stage IV values towards larger CPC analysis, consistent to the basic hypothesis of this study. In addition, both regression coefficients, a and b , show significant spatial and temporal variations. As shown in Fig. 5, the spatial variation has much larger amplitude and much more fine scale patterns over the West, especially over the mountainous areas. This is consistent with the analysis of Kursinski and Mullen (2008) on the quality of stage IV data set and suggests that the adjustment by the regression is working in the correct direction.

On the other hand, the temporal variations of the two coefficients are characterized by significant high frequency noise and kinks (Fig.6).

To deal with the above mentioned problems associated with the regression coefficients, two steps are taken to refine the slope a and intercept b separately. First, an interpolation algorithm is applied independently to a and b to fill the gaps and replace the unreliable values. For any grid box where the coefficients is missing (sample size $N < 2$) or unreliable (sample size less than a threshold, $N < N_{\min}$), the gap is filled by weighted average of the same coefficient for the grid boxes in its vicinity. This algorithm is widely used in the analysis of irregularly spaced data (Shepard 1968) such as precipitation (Xie et al. 2007). The second step is to smooth the 366 day time series of each coefficient through Fourier truncation. The raw time series is replaced by the accumulation of the first 3 harmonic components. Xie et al. (2007) used this method to remove the high frequency noises in the daily climatology of precipitation in their gauge based precipitation analysis over East Asia. Experiments with the number of the harmonic components suggest that 3 is a reasonable choice for regression coefficients, in contrast to 6 used by Xie et al. (2007) for precipitation of daily climatology. As shown in Figs. 6 and 7, the smoothed time series of a and b well represent the annual cycle and long term trend.

The choice of N_{\min} may affect this refinement of the coefficients. However, carefully checking some examples of time series suggests that interpolated values during the summer season usually do not match well with the raw values over the days before and after the filled gaps. As a result, these unrepresentative values are more subtly changed in the temporal smoothing step and the end results are not sensitive to the choice of N_{\min} . Experiments with $N_{\min}=2$ and $N_{\min}=10$ showed little difference and thus $N_{\min}=2$ is used.

d. Application of the regression to the aggregated stage IV data

The refined regression coefficients a and b are applied to adjust the aggregated Stage IV date $ST4_{L,24h}$, i.e.,

$$ST4'_{L,24h} = a' \bullet ST4_{L,24h} + b' \quad (4)$$

In Equation (4), the regression coefficients a and b are primed to indicate their difference from those calculated in (3). From Figs 5b, the slope a' is between 0.5 and 1.5 and intercept b' is in the range of -2 to 6 mm for most of the 0.125 degree grid boxes, especially over the East part of the CONUS domain. Over the west, the coefficient a can be significantly deviated from unit over areas reflecting the orographic effects, but it is between 1/7 and 7 for all points except a few. As discussed earlier, even a value as large as 100 is consistent with the records input into the regression analysis. As a result, no extreme precipitation is produced due to the abnormally large value of coefficient a . To avoid possible occurrence of this unexpected situation in the real time application, an upper limit of 500mm is set for $ST4'_{L,24h}$. On the other hand, relatively more frequent cases of negative b does result in negative precipitation in the adjusted $ST4$, i.e., $ST4'_{L,24h}$. Whenever this happens, $ST4'_{L,24h}$ is set to be zero.

e. Downscaling the adjusted precipitation in space and time

The final stage of the process is to downscale the adjusted Stage IV analysis $ST4'_{L,24h}$ in both space and time. As discussed in section 1, the goal of adjusting the Stage IV data is to retain the higher spatial and temporal resolution while making its climatology towards that of the CPC. As discussed in section 3b, a simple interpolation of $ST4'_{L,24h}$, even using the water volume conservation scheme, i.e.,

$$ST4'_{L,24h} \rightarrow ST4'_{L-H,24h} \quad (5)$$

can not achieve this goal due to the irreversibility of (2). Nevertheless, $ST4'_{L-H,24h}$ can be used as the basis for the spatial down scaling. Comparing the two fields in (2) by looking at the ratio can isolate the fine scale structures, which in turn can be posed to $ST4'_{L-H,24h}$, i.e.,

$$ST4'^*_{L-H,24h} = ST4'_{L-H,24h} \bullet \frac{ST4_{H,24h}}{ST4_{L-H,24h}} \quad (6)$$

is the result of spatial resolution recovery of the statistically adjusted stage IV analysis.

The temporal downscaling is conceptually straightforward: $ST4'^*$ is disaggregated into the four successive, non-overlapping 6-hour periods with the same proportion as that in the raw stage IV data set. Mathematically, this is the inversion of equation (1) except applied to $ST4'^*$ instead of $ST4$, i.e.,

$$ST4'^*_{H,6h} = ST4'^*_{H,24h} \bullet \frac{ST4^k_{H,6h}}{\sum_{n=1}^4 ST4^n_{H,6h}} \quad \text{for } k=1, 2, 3, 4 \quad (7)$$

In (6) and (7), the grid value for the left hand side is automatically set to zero when the denominator is zero.

4. Operational Implementation and Dataset Statues

A software package has been developed to implement the algorithm described in section 3. The first component of the package determines the regression coefficients a and b, following steps a, b and c described in section 3 and using the historical data sets of CPC and Stage IV for the period from June 1 2002 to July 31 2009. The choice of training period provides an identical potential sample size of 427 (=61x7) for all 366 days of the

year, with a 61-day window and exactly 7 years of data. In the second component of the package, the gap-filled and temporally smoothed version of regression coefficients, a' and b' , are retrieved from an archive and applied to adjust real time and historical Stage IV 6-hour accumulated precipitation analysis and processing, following steps a, d and e of the algorithm.

The later component of the software package, named Climatology-Calibrated Precipitation Analysis (CCPA) and with products of the same name, was implemented in NCEP's production suite on July 13, 2010. Since then, CCPA has been running on a real time basis to process the Stage IV 6 hour precipitation data. Following the data flow and schedule of Stage IV products, the first version of the CCPA data set for the 24-hour period ending 12 UTC is available shortly after 15 UTC and it will be updated 8 hours, 32 hours and 41 hours later. For most days, the final version is available with the first update shortly after 15 UTC the same day.

In order to take advantage of this new CCPA product, its historical archive was generated at EMC/NCEP for the period of Jan. 1, 2002 to July 13, 2010. This historical archive, combined with the real time output, is available to the meteorological/hydrological community and general public. As a calibrated version of the Stage IV 6 hour precipitation analysis, CCPA can be used in evaluation and calibration of precipitation forecast. Using the water volume conservation scheme, CCPA is converted to the 5 km National Digital Forecast Database (NDFD) grid, and latitude-longitude grids at 0.125, 0.5 and 1.0 degree resolution, all covering the CONUS domain.

5. Evaluation

To evaluate the methodology and data set described in this paper, CCPA and ST4 can be directly compared at the natural resolution of Stage IV, with 6 hour accumulations. Fig. 8 displays an example for 18 UTC , 30th to 00 UTC 31st, Dec. 2009. While the large scale precipitation patterns in ST4 (Fig.8b) and CCPA (Fig.8a) are identical, differences in the shape and size of the 10mm contour are visible in the Lower Mississippi States and Utah. In fact, the spatial pattern correlation coefficient between the two fields are always well above 0.99 (not shown).

As described in section 2, the major component of the CCPA methodology is the application of linear regression between ST4 and CPC at 0.125 degree resolution and 24 hour accumulation. Therefore, evaluation of the CCPA methodology and dataset is focused on this aspect. For this purpose, CCPA and the original Stage IV data (ST4) are aggregated to 0.125 degree resolution and 24 hour accumulation periods, and compared with CPC. As a qualitative example, Fig. 9 shows the time series of the 3 analyses for the grid point located at 42N, 102W, over the warm and wet seasons of July-August 2008 and May-Jun, 2009. Overestimation in ST4 compared with CPC for most precipitation events and phase difference between the two are clearly shown. As expected, CCPA generally follows the variation of ST4 and, in most cases, bring it towards CPC.

Quantitative evaluation of CCPA methodology and dataset requires the calculation of some statistic scores over some extended periods. For this purpose, annual average is

used in this paper. As the data sample for regression analysis is relatively small, there is a need to test the robustness of the methodology. Following an approach similar to Xie et al (2007), cross validation is performed with a data holding technique. Regression slope and intercept are re-estimated with the same sample pool as described in sections 3b and 4, except that the data for a particular one year period (July 1 to June 30 next year) are excluded, and the analysis for the same period is reproduced with these new regression coefficients. The same procedure is repeated for each of the seven exclusive and non-overlapping periods and the dataset reproduced is referred to as the Cross Validation Analysis (CVA).

Fig. 10a displays the 24 hour precipitation from CPC data set, averaged over the 1 year period of 1 July 2008 through 30 June 2009. Since the emphasis here is to evaluate how much CCPA is closer to CPC in contrast to Stage IV, the differences of Stage IV, CVA and CCPA with respect to CPC are shown in Fig. 10b, c and d, respectively. Without calibration, Stage IV has larger differences either with negative or positive values, ranging from -5.3 to 5.6 mm (Fig. 10b). Although the spatial patterns are patchy, the “bias” is apparently larger over the Missouri Basin River Forecast Center (MBRFC) area (fig. 1 and 10b) than other areas, with clear domination of overestimation and a maximum of over 5 mm. In fact, the time series in Fig. 9 are from this area. As discussed in the introduction, different RFCs using different quality control and algorithms and this leads to different statistical properties of the ST4 analysis.

Since CCPA and CVA are statistical adjustment to Stage IV in magnitude, their “biases” preserve the fine scale features of high spatial variability in Stage IV and have much smaller amplitudes, with the absolute value being less than 1 mm for almost all gridpoints. Particularly, the wide-spread large positive bias over MBRFC is significantly reduced. In addition, the improvements in CVA and CCPA are very similar to each other, suggesting that the methodology is reasonably robust and the sample size is (though marginally) sufficient for the regression analysis

Finally, to further examine the impact of the statistical adjustment and the quality of CCPA data set, CCPA, ST4 and CVA are verified against surface observations obtained from RFC rain gauge network (Zhu, 2007). These daily rain gauge reports are box-averaged to 0.125 degree and thereafter defined as RFC rain gauge analysis. Root Mean Square Error (RMSE) and Absolute Mean Error (ABSE) of 24-hour precipitation are calculated against RFC rain gauge analysis as a function of threshold. For each threshold value, all of the grid points where the RFC rain gauge analysis is less than the value are not included in the calculation. These statistical scores are calculated at 0.125 degree over the CONUS domain and averaged over each of the seven exclusive and non-overlapping one-year periods. The results for the last period are shown in Fig. 11. For all grid points with observed precipitation (threshold 0.0 or 0.2 mm) there are clear improvements in terms of RMSE in both CCPA and CVA over the raw Stage IV data, with a reduction of 0.27mm for CCPA and 0.11mm for CVA. The improvements are evident mostly for lower thresholds up to 15 mm/day. For large precipitation amount (35 and 50 mm), the improvement by CCPA is less impressive. For thresholds greater than 20 mm, CVA is

not as good as ST4. The Statistics in terms of ABSE, though less gap among the 3 lines, still leads to identical conclusions. The deterioration of CVA at higher thresholds suggests that the 61-day window in the sample pool of the regression analysis is necessary with the relatively short ST4 archive and caution must be practiced in the application of CCPA with heavy precipitation events.

6. Summary and Further Discussions

A simple linear regression method is employed to statistically calibrate the multi-sensor Stage IV precipitation analysis over the CONUS domain and make its climatology closer to that of the rain gauge based analysis of CPC Unified Global Daily Gauge Analysis. Available archived historical date sets of the two analyses with a 7 year length are used to estimate the regression coefficients for each Julian day of the year and each grid point in the CPC grid mesh over CONUS. These coefficients are then applied to the spatially and temporally aggregated STAGE-IV data to generate an adjusted value, which is then down scaled in space and time to the original grid and accumulation period of Stage IV. Carefully designed interpolation/extrapolation algorithms are used to aggregate the raw STAGE-IV data and downscale the statistically adjusted value. The procedure, referred as Climatology-Calibrated Precipitation Analysis (CCPA) was implemented to the NCEP production suite on July 13, 2010, to routinely process incoming Stage IV 6 hour precipitation analysis to generate corresponding CCPA files. It is also used to process the historical Stage IV data set covering the period of Jan. 1, 2002 to July 13, 2010, to form a complete archive of CCPA.

The reason for the non-uniform behavior of the CCPA data set can be revealed by scatter plots of Stage IV analysis against CPC for each grid point and each Julian day. In a typical case, the slope of the empirical “regression” line is different for the lower and higher precipitation ranges. As heavy precipitation event is scarce, a “linear” regression is always dominated by the lower precipitation points. In other words, the merit of the methodology is limited by the weakness of the simple linear regression model and inadequate sample of high amount of precipitation. Cross validation suggests that the current estimation of regression coefficients is fairly robust with the current 7 years archived data over all precipitation events, but may be inadequate for heavy rainfall amounts. Therefore, the quality of CCPA should be improved in the future by increasing the length of the archived CPC and Stage IV data sets and using a more realistic regression model. There is a plan at EMC/NCEP to perform annual updating of the regression coefficients with increased sample size, and employ non-linear regression models or other calibration methods in the future.

Acknowledgements: The authors thank Stephan Lord, Bill Lapenta, John Ward and Geoff Dimego for their supports and advices with the methodology and datasets used in this research. Thanks are also due to Julie Demargne and John Shakee for discussions about the results of the study. M. Charles and Y. Luo are supported by NOAA Office of Hydrological Development through the joint OHD/NCEP THORPEX-HYDRO plan. The first author was partially supported by NOAA THORPEX program.

REFERENCES

- Arkin, P. A., and B. N. Meisner, 1987: The relationship between large-scale convective rainfall and cold cloud cover over the western hemisphere during 1982-1984. *Mon. Wea. Rev.*, **115**, 51-74.
- Chen, F., K. W. Manning, M. A. LeMone, S. B. Trier, R. Roberts, M. Tewari, T. W. Horst, S. P. Oncley, J. G. Alfieri, P. D. Blanken, D. Niyogi and J. B. Basara, 2007: Description and evaluation of the characteristics of the NCAR high-resolution land data assimilation system. *J. Appl. Meteor. And Clim.*, **46**, 694-713.
- Chen, M., R. E. Dickinson, X. Zeng, and A. N. Hahmann, 1996: Comparison of precipitation observed over the continental United States to that simulated by a climate model. *J. Climate*, **17**, 930-951.
- Chen, M., P. Xie and J. E. Janowiak, 2002: Global land precipitation: A 50-yr Monthly analysis based on gauge observations. *J. Hydrometeor.*, **3**, 249-266.
- Dai, A., I. Y. Fung, and A. D. del Genio, 1997: surface observed global land precipitation variations during 1900-1988. *J. Climate*, **10**, 2943-2962.
- Ebert, E. E., and M. J. Manton, 1998: Performance of satellite rainfall estimation algorithms during TOGA COARE. *J. Atmos. Sci.*, **55**, 1537-1557.
- Fekete, B. M., C. J. Vorosmarty, J. O. Roads, and C. J. Willmott, 2004: Uncertainties in precipitation and their impacts on runoff estimates. *J. Climate*, **17**, 294-304.
- Ferraro, R. R., 1997: Special sensor microwave image derived global rainfall estimates for climatological applications. *J. Geophys. Res.*, **102**, 16 715-16 735.
- Higgins, R. W., W. Shi, E. Yarosh, and R. Joyce, 2000: Improved United States precipitation quality control system and analysis. NCEP/Climate Prediction Center Atlas, No. 7, National Oceanic and Atmospheric Administration, National Weather Service. [available online at http://www.cpc.ncep.noaa.gov/research_papers/ncep_cpc_atlas/7/index.html].
- Huffman, G. L., and coauthors, 1997: The global precipitation Climatology Project (GPCP) combined precipitation dataset. *Bull. Amer. Meteor. Soc.*, **78**, 5-20.
- Kummerow, C., and Coauthors, 2000: The status of the tropical rainfall measuring mission (TRMM) after two years in orbit. *J. Appl. Meteor.*, **39**, 1965-1982.
- Kursinski, A. and S. Mullen, 2008: Spatiotemporal variability of hourly precipitation over the eastern Contiguous United States from stage IV multisensory analysis. *J. Hydrometeor.*, **9**, 3-21.

- Lin, Y., and K. E. Mitchell, 2005: The NCEP stage II/IV hourly precipitation analyses: Development and applications. Preprints, *19th Conf. on Hydrology*, San Diego, CA, Amer. Meteor. Soc., 1.2.
- Maddox, R. A., and J. Zhang, J. J. Gourley, and K. W. Howard, 2002: weather radar coverage over the contiguous United States. *Wea. Forecasting*, **17**, 927-934.
- McCollum, J., W. F. Krajewski, R. R. Ferraro, and M. B. Ba, 2002: Evaluation of biases of satellite rainfall estimation algorithms over the continental United States. *J. Appl. Meteor.*, **41**, 1065-1081.
- New, M., M. Hulme, and P. Jones, 2000: Representing twentieth-century space-time climate variability. Part II: Development of 1901-96 monthly grids of terrestrial surface climate. *J. Climate*, **13**, 2217-2238.
- Nijssen, B., G. M. O'Donnel, and D. P. Lettenmaier, 2001: Predicting the discharge of global rivers. *J. Climate*, **14**, 3307-3323.
- Onof, C., and H. S. Wheeler, 1996: Analysis of the spatial coverage of British rainfall fields. *J. Hydrol.* **176**, 97-113.
- Seo, D.-J. and J. P. Breidenbach, 2002: Real-time correction of spatially nonuniform bias in radar rainfall data using rain gauge measurements. *J. Hydrometeor.*, **3**, 93-111.
- Shepard, D., 1968: A two dimensional interpolation function for irregularly spaces data. Proc. 23rd National Conf. of the Association for Computing machinery, Princeton, NJ, ACM, 517-524.
- Spencer, R. W., 1993: Global oceanic precipitation from MSU during 1979-91 and comparisons to other climatologies. *J. Climate*, **6**, 1301-1326.
- Susskind, J., P. Piraino, L. Rokkle, and A. Mehta, 1997: Characteristics of the TOVS pathfinder Path A dataset. *Bull. Amer. Meteor. Soc.*, **78**, 1449-1472.
- Wilneit, T. J., A. T. C. Channg, and L. S. Chiu, 1991: Retrieval of monthly rainfall indices from microwave radiometric measurements using probability distribution functions. *J. Atmos. Oceanic Technol.*, **8**, 118-136.
- Xie, P., and P. A. Arkin, 1996: Analysis of global monthly precipitation using gauge observations, satellite estimates and numerical model predictions. *J. Climate*, **9**, 840-858.
- Xie, P., and P. A. Arkin, 1997: Global precipitation: A 17-year monthly analysis based on gauge observations, satellite estimates and numerical model outputs. *Bull. Amer. Meteor. Soc.*, **78**, 2539-2558.

- Xie, P., and P. A. Arkin, 1998: Global monthly precipitation estimates from satellite-observed outgoing longwave radiation. *J. Climate*, **11**, 137-164.
- Xie, P., A. Yatagai, M. Chen, T. Hayasaka, Y. Fukushima, C. Liu and S. Yang, 2007: A Gauge-based analysis of daily precipitation over East Asia. *J. Hydrometeor.*, **8**, 607-626.
- Xie, P., J. E. Janowiak, P. A. Arkin, R. Arkin, R. Adler, A. Gruber, R. Ferraro, G. J. Huffman, and S. Curtis, 2003: GPCP pentad precipitation analyses: An experimental dataset based on gauge observations and satellite estimates. *J. Climate*, **16**, 2197-2214.
- Xie P, M. Chen M and W. Shi, 2010: CPC unified gauge analysis of global daily precipitation. (To be submitted)
- Zhao, Q. and Y. Jin, 2008: High-resolution radar data assimilation for hurricane Isabel (2003) at landfall. *Bull. Amer. Meteor. Soc.*, **89**, 1355-1372.
- Zhu, Y. 2007: Objective Evaluation of Global Precipitation Forecast. In special collection of: *International Symposium on Advances in Atmospheric Science and Information Technology*, Beijing, China, 2007 p3-8.

Figure Captions

Fig.1 The domains of the thirteen River Forecast Centers (RFC). Note that stage IV analysis covers the twelve RFCs over the Contiguous United States (CONUS). Image from http://www.srh.noaa.gov/lub/wx/wns_HSAs.htm.

Fig.2 The 24 hour precipitation from 0.125 degree CPC analysis for may 20th, 2006 (upper panel) and stage IV analysis aggregated to the same grid and accumulation time period.

Fig.3 (a) The actual sample size (upper panel) and residual error of regression for Jan. 1st.

Fig. 3 (b) Same as fig.3 (a) except for July 1st.

Fig.4 time series of sample size and residual error of the analysis for a grid point in the Southwest, with empty samples during the summer months.

Fig. 5 (a) Regression coefficients a and b, for Aug. 1, Calculated from Equation (3).

Fig. 5 (b) Regression coefficients a and b for Aug. 1 after gap filling.

Fig.6. Time series of regression coefficient a for four selected grid points. Gap filled value (black) and the smoothed version (green).

Fig.7. Time series of regression coefficient b for four grid points. Gap filled value (black) and the smoothed version (green).

Fig. 8. The 6 hour precipitation from (a) CCPA at 4km HRAP grid accumulated for the period of 18Z , 30th to 00Z 31st, December 2009 and (b) Stage IV analysis at the same grid and accumulation time period.

Fig. 9 Time series of 24 hour precipitation at point (42N, 102W) from 0.125 degree CPC UPA(short dash line), Stage IV (dot and dash line) and CCPA (solid line) for two periods: (a) 1 July – 31 August 2008; (b) 1 May – 30 June 2009.

Fig. 10. (a) The 24 hour precipitation from 0.125 degree CPC averaged between 1 July 2008 and 30 June 2009 and The differences of (b) Stage IV, (c) CVA and (d) CCPA with respect to CPC. Stage IV, CVA, and CCPA are aggregated to the same grid and accumulation time period.

Fig. 11. Root Mean Square Error (RMSE, solid line) and Absolute Mean Error (ABSE, dotted line) of 24-hour precipitation from Stage IV (black), CVA (red) and CCPA (green) verified against RFC rain gauge analysis as a function of precipitation threshold.

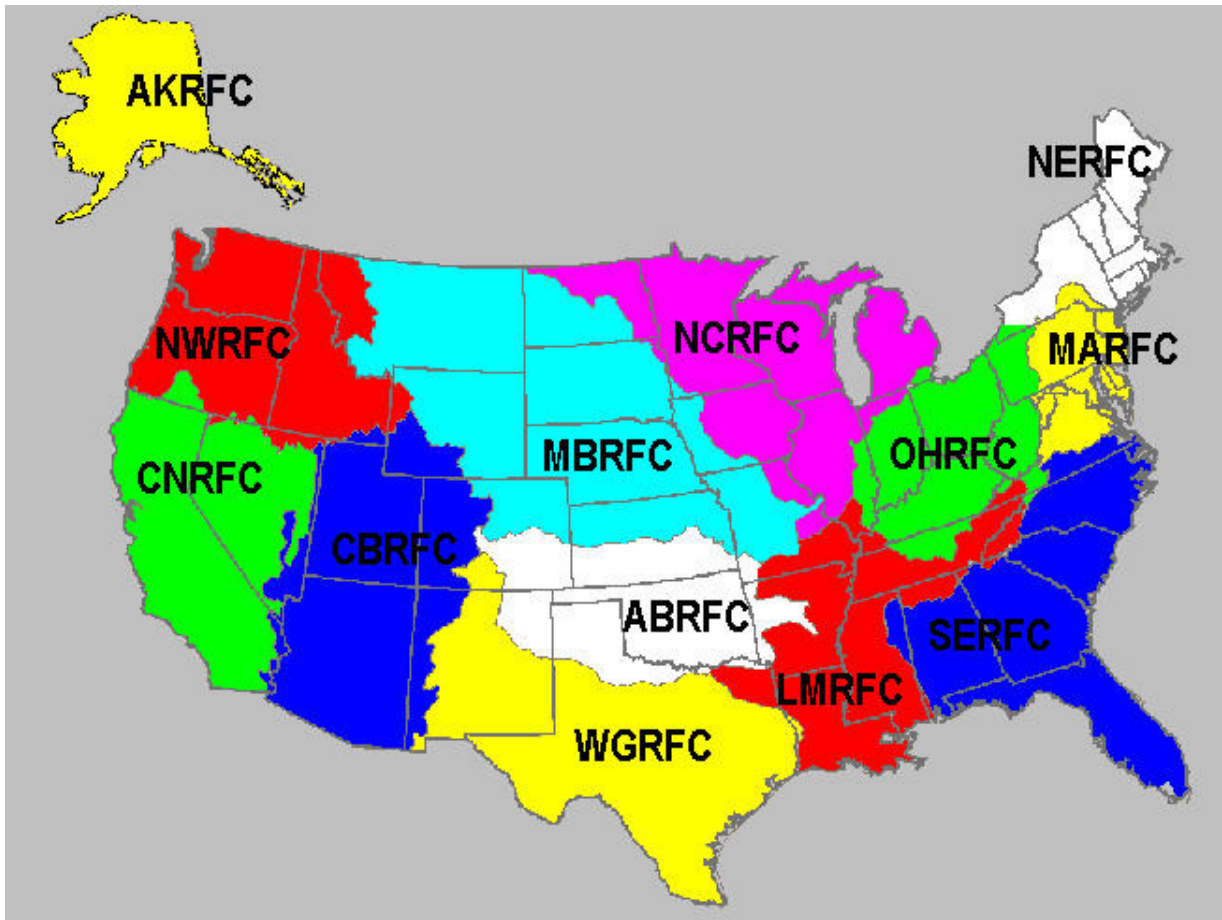


Fig.1 The domains of the thirteen River Forecast Centers (RFC). Note that stage IV analysis covers the twelve RFCs over the Contiguous United States (CONUS). Image from http://www.srh.noaa.gov/lub/wx/nws_HSAs.htm.

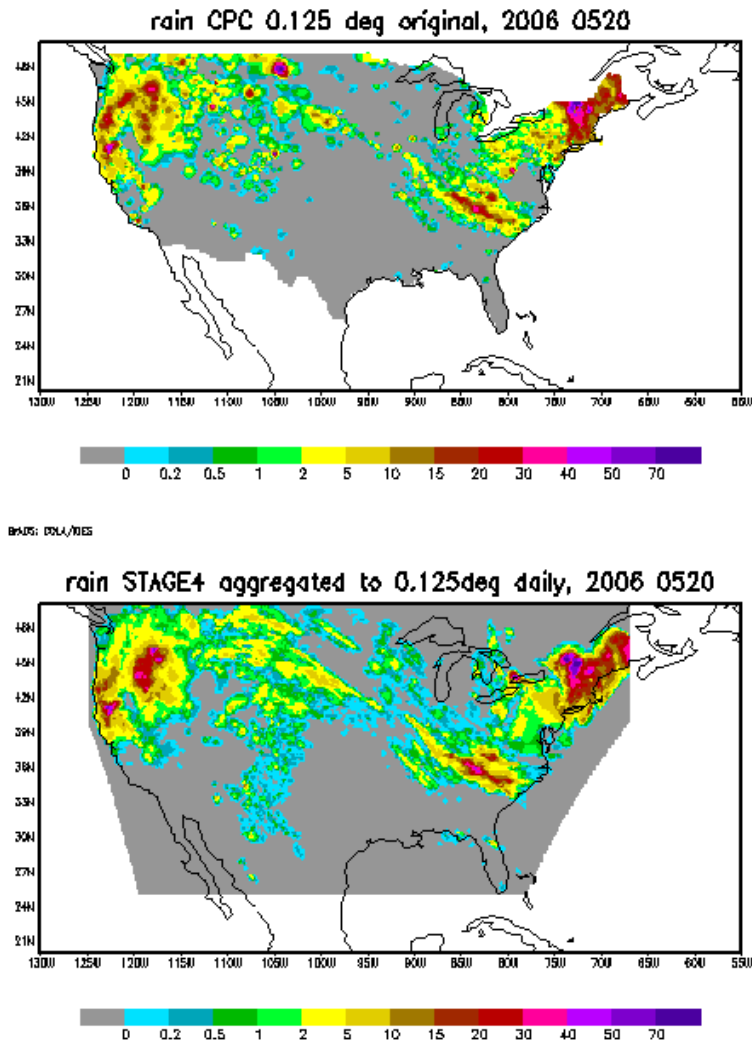


Fig.2 The 24 hour precipitation from 0.125 degree CPC analysis for may 20th, 2006 (upper panel) and stage IV analysis aggregated to the same grid and accumulation time period.

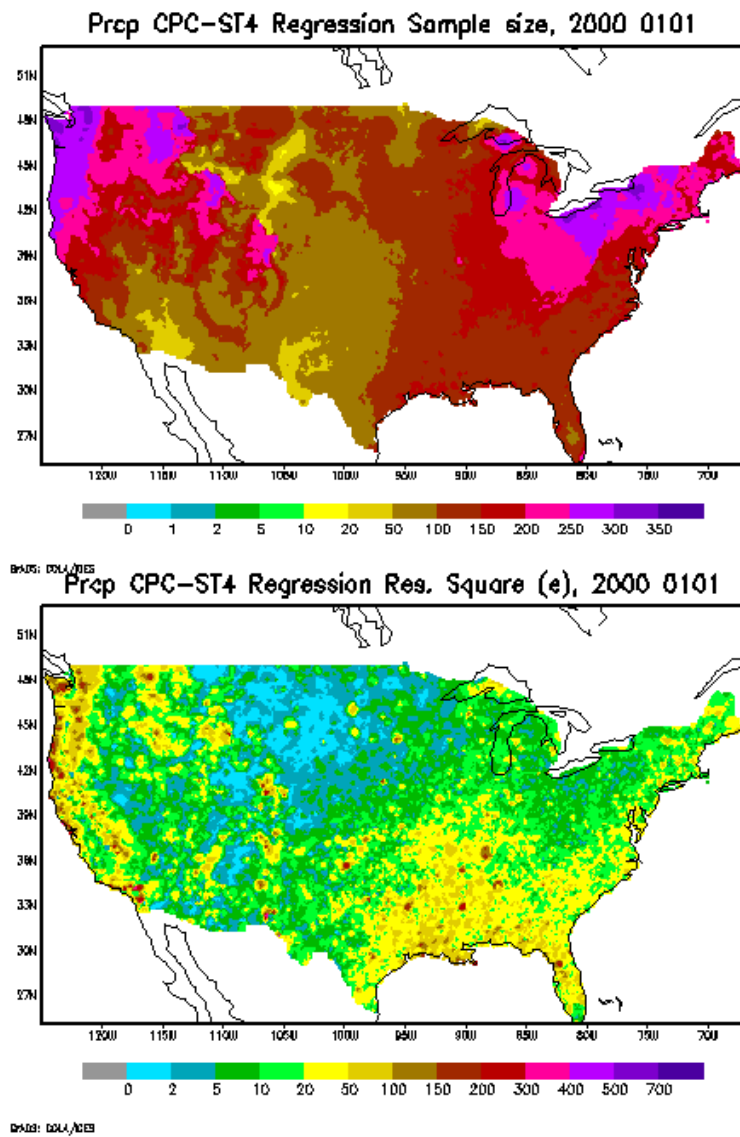


Fig. 3. (a) The actual sample size (upper panel) and residual error of regression for Jan. 1st.

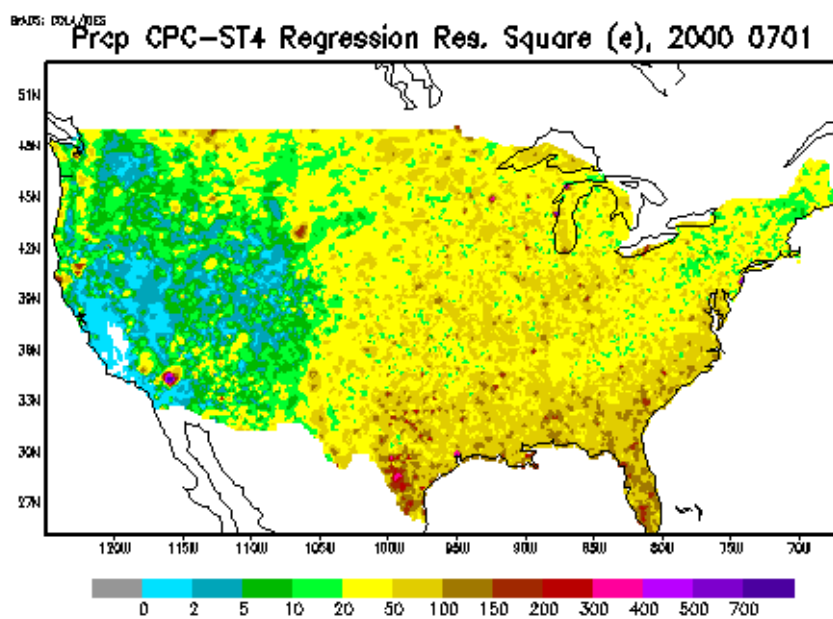
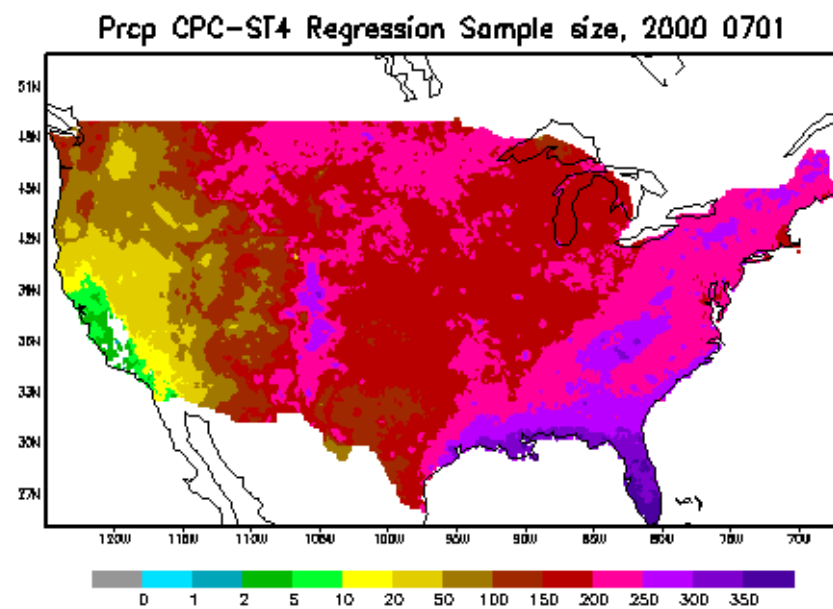


Fig. 3(b) Same as fig.3 (a) except for July 1st.

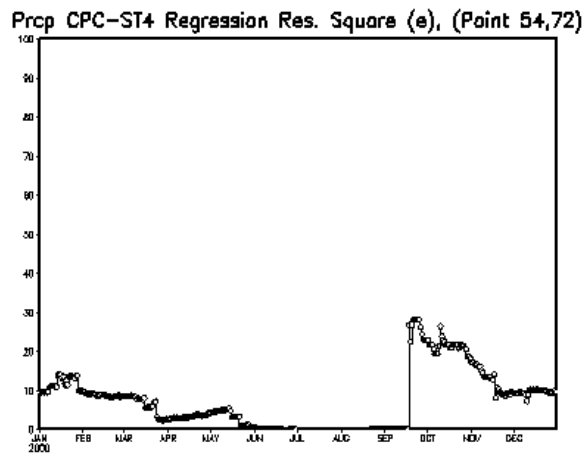
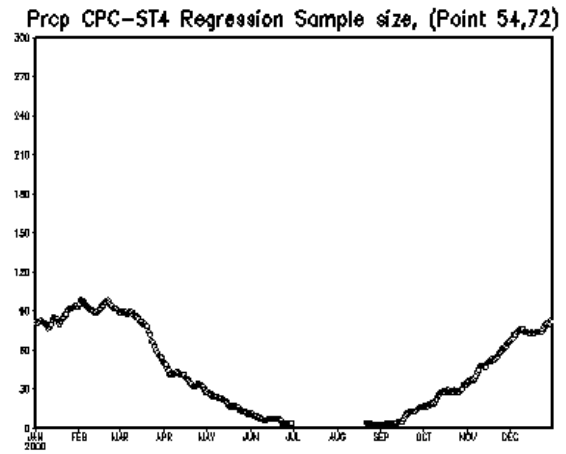


Fig.4 time series of sample size and residual error of the analysis for a grid point in the Southwest, with empty samples during the summer months.

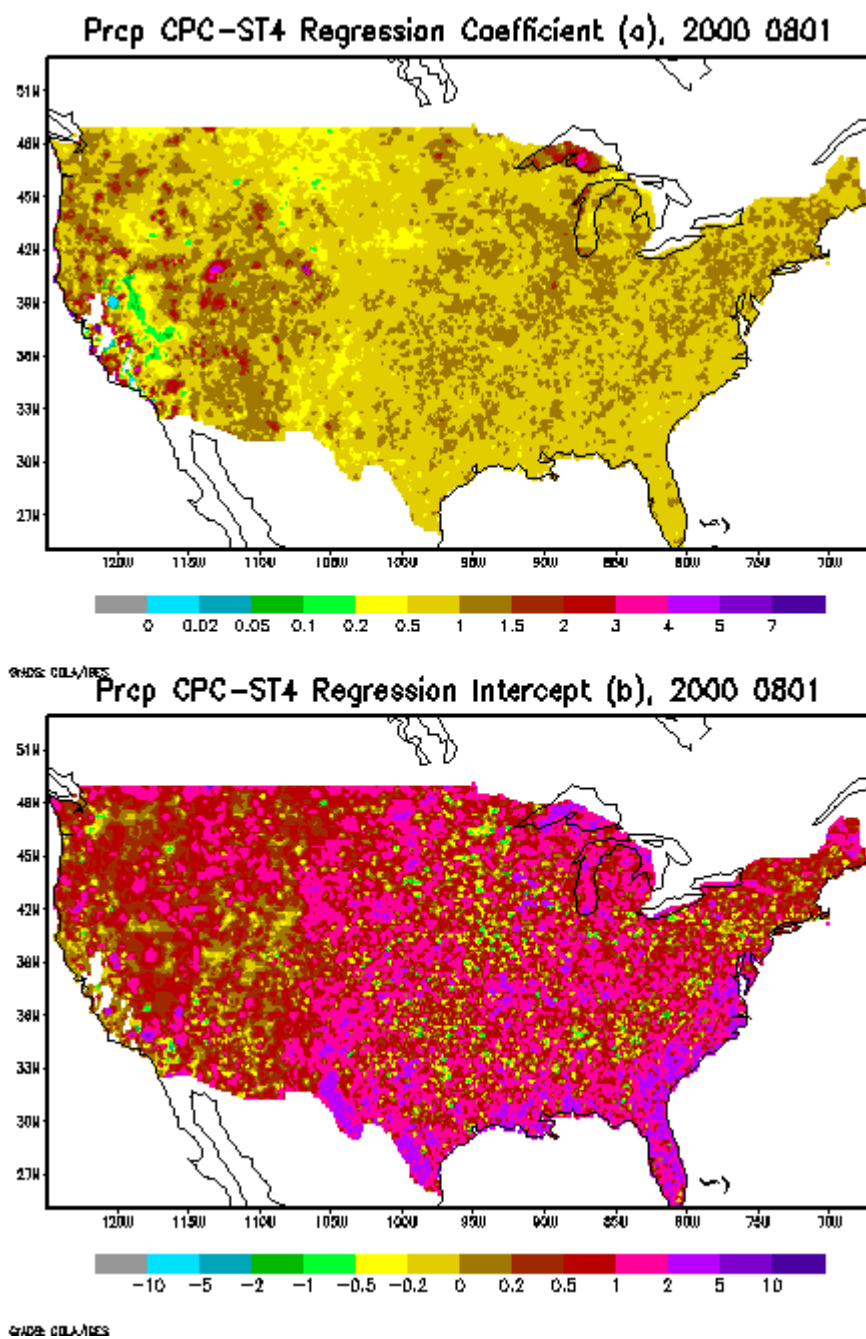


Fig. 5 (a) Regression coefficients a and b, for Aug. 1, Calculated from Equation (3).

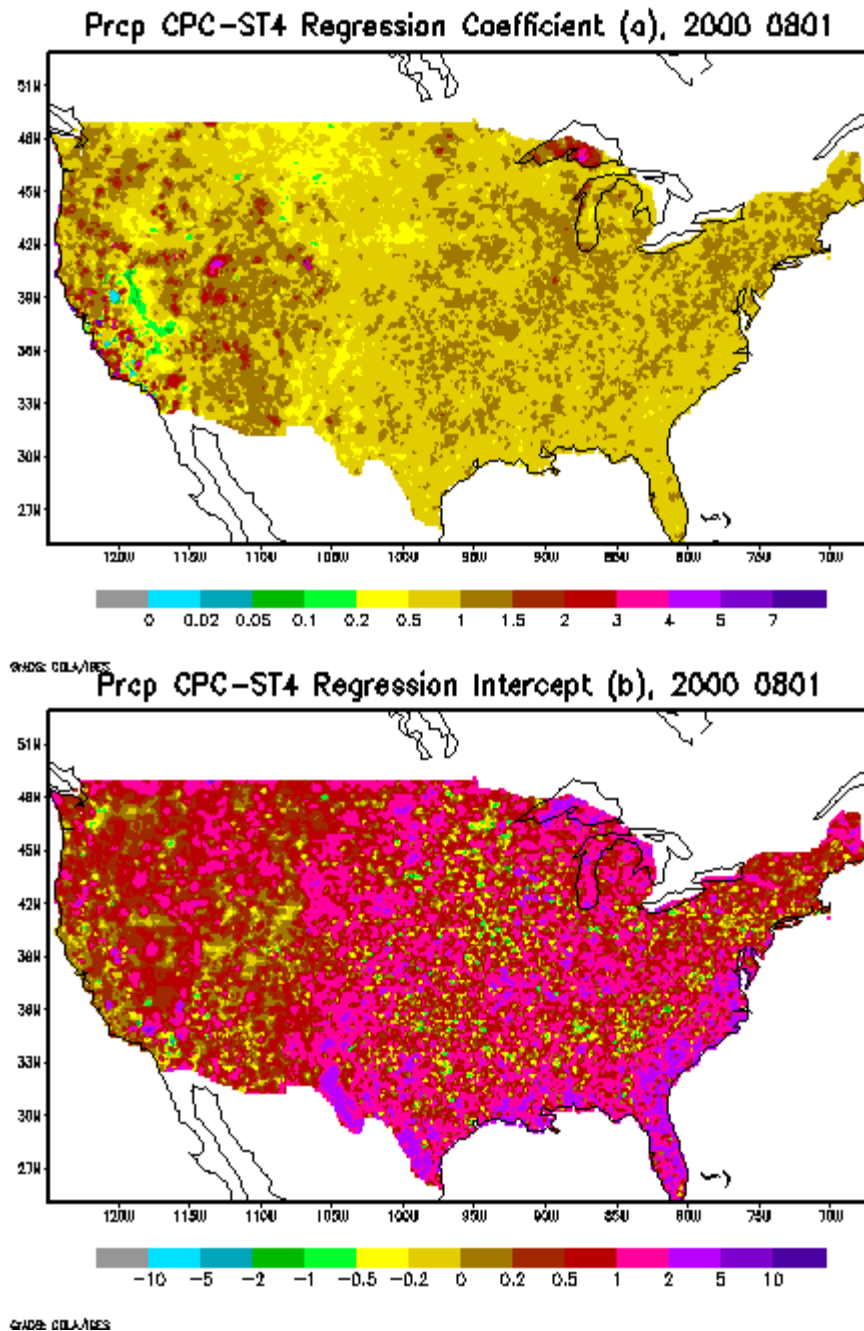


Fig. 5 (b) Regression coefficients a and b for Aug. 1 after gap filling.

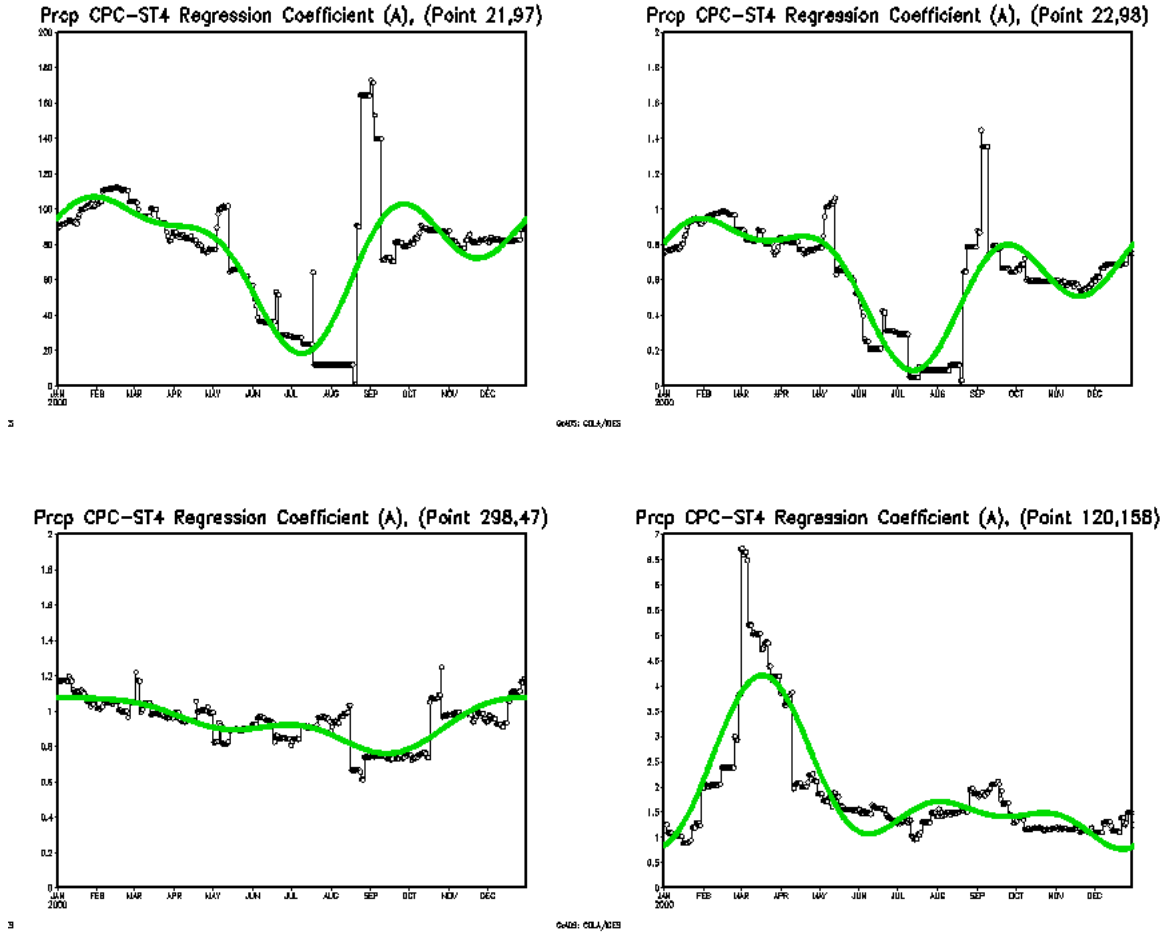
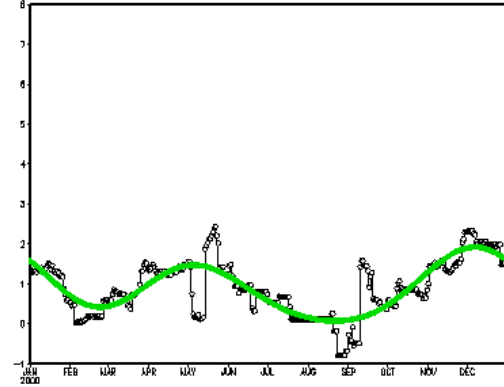


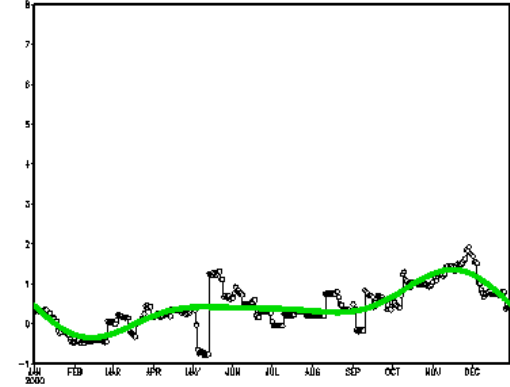
Fig.6. Time series of regression coefficient a for four selected grid points. Gap filled value (black) and the smoothed version (green).

Prp CPC-ST4 Regression Coefficient (B), (Point 21,97)

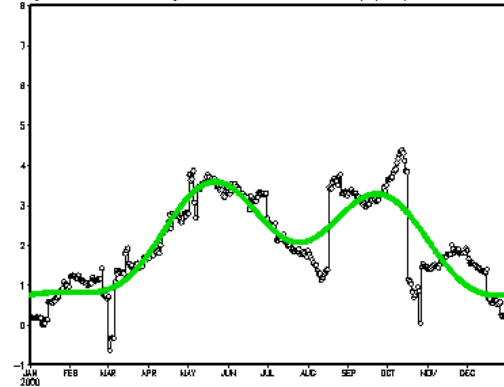


94495: GOLA/9103

Prp CPC-ST4 Regression Coefficient (B), (Point 22,98)



Prp CPC-ST4 Regression Coefficient (B), (Point 298,47)



94495: GOLA/9103

Prp CPC-ST4 Regression Coefficient (B), (Point 120,158)

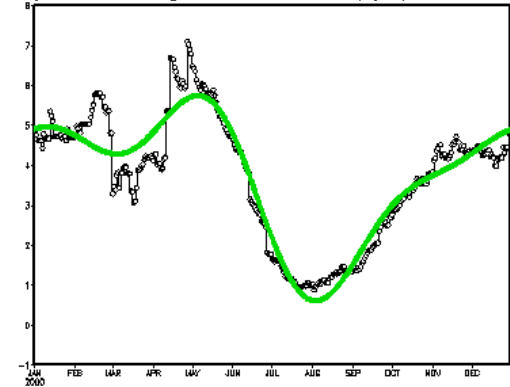


Fig.7. Time series of regression coefficient b for four grid points. Gap filled value (black) and the smoothed version (green).

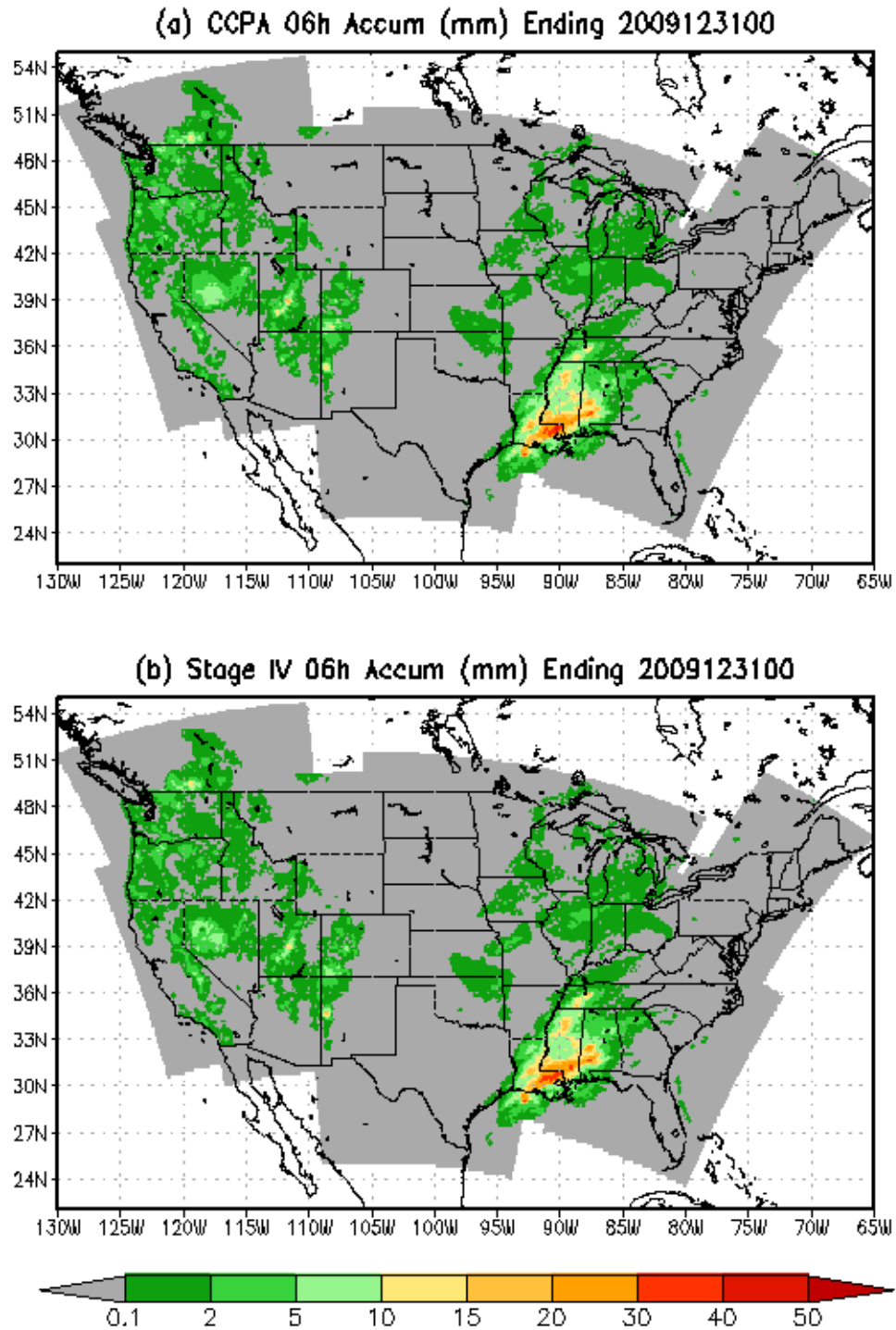


Fig. 8. The 6 hour precipitation from (a) CCPA at 4km HRAP grid accumulated for the period of 18Z , 30th to 00Z 31st, December 2009 and (b) Stage IV analysis at the same grid and accumulation time period.

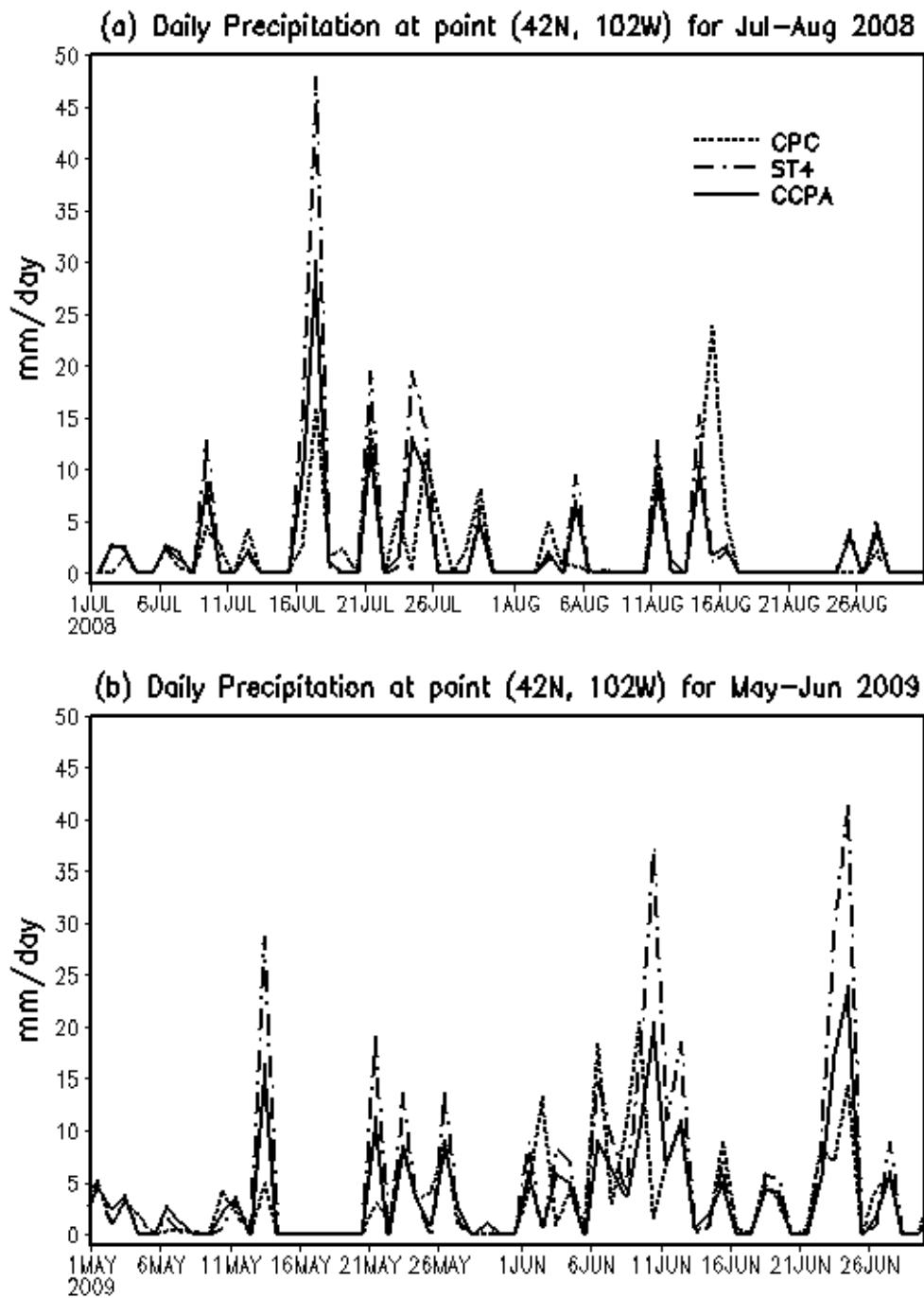


Fig. 9 Time series of 24 hour precipitation at point (42N, 102W) from 0.125 degree CPC UPA(short dash line), Stage IV (dot and dash line) and CCPA (solid line) for two periods: (a) 1 July – 31 August 2008; (b) 1 May – 30 June 2009.

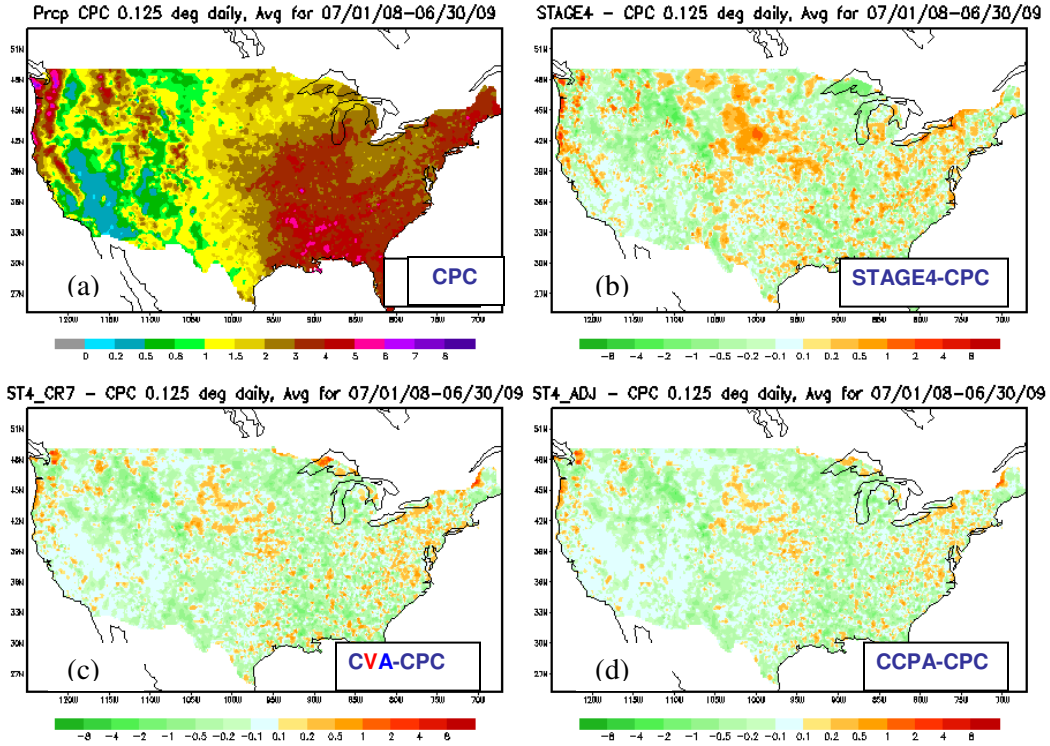


Fig. 10. (a) The 24 hour precipitation from 0.125 degree CPC averaged between 1 July 2008 and 30 June 2009 and The differences of (b) Stage IV, (c) CVA and (d) CCPA with respect to CPC. Stage IV, CVA, and CCPA are aggregated to the same grid and accumulation time period.

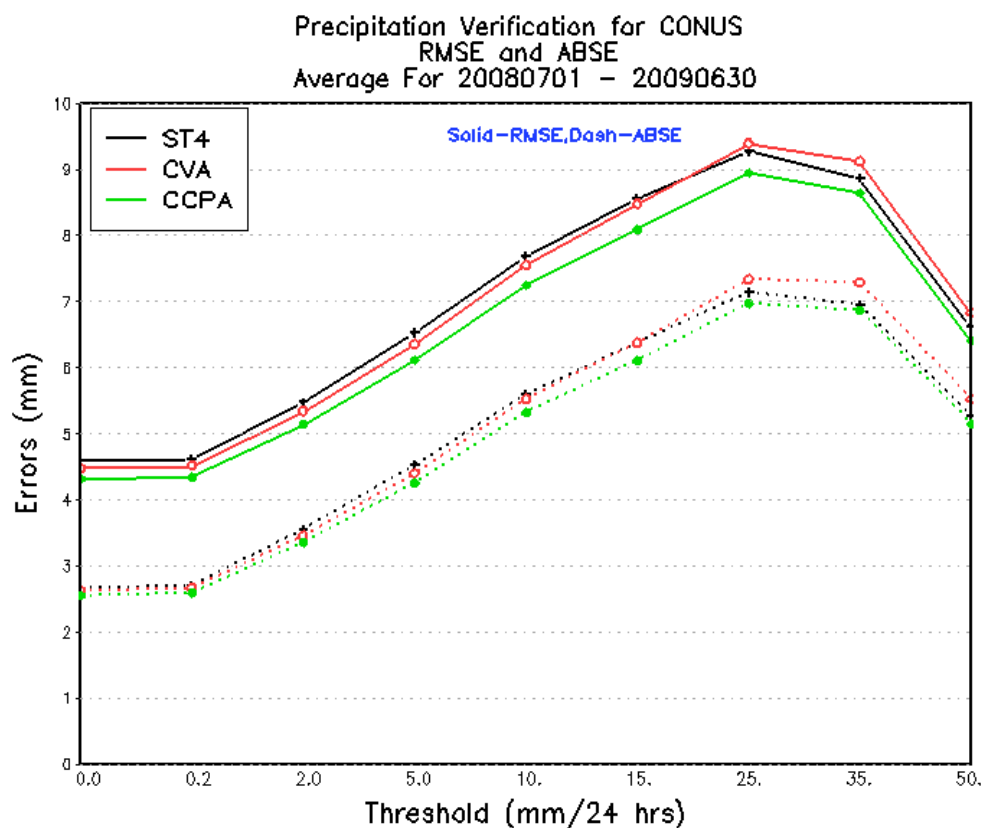


Fig. 11. Root Mean Square Error (RMSE, solid line) and Absolute Mean Error (ABSE, dotted line) of 24-hour precipitation from Stage IV (black), CVA (red) and CCPA (green) verified against RFC rain gauge analysis as a function of precipitation threshold.